MIMO RADAR DETECTION WITH HETEROGENEOUS PROPAGATION LOSSES

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ABSTRACT
A multiple-input multiple-output (MIMO) radar can utilize distributed antennas to improve detection performance. Some existing works model bistatic path gains as identically and independently distributed random variables, and the known distinct features between propagation paths are neglected. Based on the bistatic radar equation, a path gain is a product of target reflection gain and propagation loss. Since the latter depends on geometry and system parameters, the true path gains are not necessarily identically distributed. In this paper, the propagation loss is incorporated into the MIMO radar signal model and the binary hypothesis test is explored. The test statistic is a sum of weighted Chi-square random variables under either hypothesis, and its distribution is a Gamma mixture. The statistic is a sum of weighted Chi-square random variables under either hypothesis, and its distribution is a Gamma mixture. The probabilities of detection and false alarm can be explicitly obtained. In addition, a saddlepoint approximation based performance analysis is suggested, and it may be less sensitive to numerical errors, particularly when weighting coefficients are similar.

Index Terms— Neyman-Pearson, saddlepoint approximation, Chi-square, Gamma mixture, bistatic radar equation.

1. PROBLEM STATEMENT
Multiple-input multiple-output (MIMO) radar systems emphasize illumination and receiving cooperation, and they may outperform monostatic ones on target detection and estimation [1–5]. Based on antenna configuration, MIMO radars can be roughly categorized as either co-located or statistical: the former implies coherent processing such as beamforming [1], while the latter stresses the diversity of path gains with dissimilar transmitter-receiver geometries [2].

Most statistical MIMO radars share two key features: a distributed antenna configuration, and an orthogonal waveform set. A distributed setup allows simultaneous probing of a target from different bistatic angles to combat radar cross section fluctuation. Let $N_t$ and $N_r$ respectively denote the numbers of transmitters and of receivers. The collected echo of a receiver is the superposition of $N_t$ independently attenuated signals; an orthogonal waveform set would seem ideal to separate them. Via a matched filter bank, $N_tN_r$ path gains are obtained, and then noncoherent detection follows.

MIMO radar detection has been widely investigated, see for example [2–4]. In those works, path gains are modeled as random scalars, and they are assumed to be independently and identically distributed (i.i.d.). Their spatial distinction is neglected. A real bistatic path gain is a product of target strength gain and propagation loss [6, p.68]. Since the latter is a function of bistatic geometry and system parameters, real path gains are not necessarily identically distributed. In this paper, we integrate propagation losses into the MIMO radar signal model, and derive the statistic—a weighted sum of independent Chi-square random variables—for the binary hypothesis test. The probability density function (pdf) of the test statistic is a Gamma mixture under either the null or the alternative hypothesis [7], and the exact formulas for the probabilities of detection and of false alarm are available. The exact analysis is based on partial fraction expansion (PFE), which is numerically sensitive when the weighting coefficients are close [8]. To alleviate it, a saddlepoint approximation (SA) [9] is suggested. The rest of this paper is as follows. Section 2 proposes the MIMO radar signal model including propagation loss. Section 3 formulates the binary hypothesis test and analyzes its detection performance. The SA based detection analysis is given in Section 4, while power allocation is discussed in Section 5. Numerical results are shown in Section 6, and conclusions are drawn after that.

2. SIGNAL MODEL
Based on the bistatic radar equation [6, p.68], a true path gain incorporates the target reflection gain, say $g_{i,j}$ for receiver $i$ and transmitter $j$, and the propagation loss, say $p_{i,j}$. If all antennas are sufficiently separated, the $g_{i,j}$’s are independent for different bistatic constellations [2]. Moreover, if the target is comprised of a large number of i.i.d. random scatterers (i.e. Swerling target models I and II), $g_{i,j}$’s can be modeled as i.i.d. zero-mean complex Gaussian random variables [2,3]. The propagation loss $p_{i,j}$ is a function of waveform propagation distance and antenna features [6, p.68]

$$p_{i,j} = \frac{\kappa}{d_j^2 d_i^2 \sqrt{A_i A_t}}, \quad (1)$$

where $\kappa$ is a constant, $d_j^2$ (or $d_i^2$) denotes the distance between the target and transmitter $j$ (receiver $i$), while $A_i$ and $A_t$ denote the transmission and receiving antenna gains, respectively. Obviously, the $p_{i,j}$’s exhibit geometry and antenna diversities, and they may have different values. As a result, the path gains, the products $(p_{i,j}g_{i,j})$’s, are not necessarily identically distributed.

Suppose that the emitted waveform of the $j$th transmitter is $\sqrt{E_j} s_j(t)$, where $\int |s_j(t)|^2 dt = 1$ and $E_j > 0$ stands for the transmission power, and then the collected echoes from a single point target, of which the Doppler effect is negligible, at receiver $i$ is

$$y_i(t) = \sum_{j=1}^{N_t} p_{i,j} g_{i,j} \sqrt{E_j} s_j(t - \tau_{i,j}) + w_i(t), \quad (2)$$

where $g_{i,j}$’s $\sim \mathcal{CN}(0, \sigma_j^2)$, $\tau_{i,j}$ stands for the time delay, and $w_i(t)$ incorporates clutter and noise. Let $y_i(t)$ go through a matched filter with time response $s_k^*(\cdot)$, and its output is expressed as $\hat{y}_{i,k}(t) = \int y_i(\eta) s_k^*(\eta - t) d\eta$. Following [2], a perfect orthogonal waveform
basis set is assumed available: \( \int s_j(\eta) s_j^*(\eta + t) d\eta \equiv 0 \) for \( j \neq k \).
Therefore, \( \tilde{y}_{i,k}(t) \) shall be simplified as
\[
\tilde{y}_{i,k}(t) = p_{i,k} g_i \sqrt{E_0} \int s_k(\eta - \tau_{i,k}) s_k^*(\eta - t) d\eta + \tilde{w}_{i,k}(t),
\]
where \( \tilde{w}_{i,k}(t) = \int w_i(\eta) s_k^*(\eta - t) d\eta \). Sampling \( \tilde{y}_{i,k}(t) \) at \( \tau_{i,k} \), we obtain
\[
x_{i,k} \equiv \tilde{y}_{i,k}(\tau_{i,k}) = p_{i,k} g_i \sqrt{E_0} + n_{i,k},
\]
where \( n_{i,k} = \tilde{w}_{i,k}(\tau_{i,k}) \). Note that if the transmitters are omnidirectional, \( \tau_{i,k} \) is generally unavailable as one may not know where echoes are from. However, if the transmitters have certain beamforming capability and they cooperatively search a certain spatial cell of interest under beam synchronization, the \( \tau_{i,k} \)’s are available. In addition, suppose that all receivers are homogeneous and that \( w(t) \)’s are i.i.d. complex zero-mean white Gaussian noise with power density \( \sigma_w^2 \). It is easy to obtain that \( n_{i,k} \)’s are i.i.d. complex Gaussian variables with \( n_{i,k} \sim \mathcal{CN}(0, \sigma_w^2) \) [10].

**3. DETECTION**

### 3.1. Binary Hypothesis Test

Let the received signal at each receiver be processed by a bank of filters, of which the time responses are \( s_j(t) \) respectively, where \( 1 \leq j \leq N_t \), and then the MIMO radar system shall acquire \( N_t \times N_r \) output samples. The target detection problem at a spatial cell of interest is a binary hypothesis test
\[
\mathcal{H}_0: \quad x_{i,j} = n_{i,j} \\
\mathcal{H}_1: \quad x_{i,j} = p_{i,j} g_i \sqrt{E_j} + n_{i,j}
\]
for \( 1 \leq i \leq N_t \) and \( 1 \leq j \leq N_r \), and the centralized likelihood ratio test is formulated as
\[
\prod_{j=1}^{N_r} \prod_{i=1}^{N_t} \left| \frac{f(x_{i,j}|\mathcal{H}_1)}{f(x_{i,j}|\mathcal{H}_0)} \right|^{\eta_1} \mathcal{H}_0 \equiv \eta,
\]
where \( \eta \) is the threshold. Since \( x_{i,j}|\mathcal{H}_0 \sim \mathcal{CN}(0, \sigma_w^2) \) and \( x_{i,j}|\mathcal{H}_1 \sim \mathcal{CN}(0, \sigma_w^2 + \sigma_p^2 p_{i,j}^2 E_j) \), the optimal test can be equivalently written as
\[
T = \sum_{j=1}^{N_r} \sum_{i=1}^{N_t} |x_{i,j}|^2 \mathcal{H}_0 \quad \sum_{j=1}^{N_r} \sum_{i=1}^{N_t} \frac{2p_{i,j}^2 E_j}{\sigma_w^2 + \sigma_p^2 p_{i,j}^2 E_j} \eta \mathcal{H}_0
\]
Furthermore, as \( |x_{i,j}|^2 \sim \frac{\sigma_w^2}{2}\chi^2_2 \) under \( \mathcal{H}_0 \) while \( |x_{i,j}|^2 \sim \frac{\sigma_w^2 + \sigma_p^2 p_{i,j}^2 E_j}{2}\chi^2_2 \) under \( \mathcal{H}_1 \), where \( \chi^2_2 \) represents the Chi-square distribution with \( k \) degrees of freedom, \( T \) is recast as
\[
T = \left\{ \begin{array}{ll}
\sum_{j=1}^{N_r} \sum_{i=1}^{N_t} \psi_{i,j} z_{i,j} & \mathcal{H}_0 \\
\sum_{j=1}^{N_r} \sum_{i=1}^{N_t} \phi_{i,j} z_{i,j} & \mathcal{H}_1
\end{array} \right.
\]
where \( z_{i,j} \)’s \( \sim \chi^2_2 \) are independent random variables,
\[
\psi_{i,j} = \frac{\sigma_w^2 p_{i,j}^2 E_j}{\sigma_w^2 + \sigma_p^2 p_{i,j}^2 E_j} \geq 0, \quad \phi_{i,j} = p_{i,j}^2 E_j > 0.
\]
Clearly, \( T \) is a positively weighted sum of i.i.d. Chi-square random variables under either hypothesis. As \( \psi_{i,j} \) is a monotonically increasing function of \( \phi_{i,j} \), we have
\[
\psi_{i,j} = \psi_{i,k} \Leftrightarrow \phi_{i,j} = \phi_{i,k} \quad \text{and} \quad \psi_{i,j} \neq \psi_{i,k} \Leftrightarrow \phi_{i,j} \neq \phi_{i,k},
\]
where ‘\( \Leftrightarrow \)’ denotes mathematical equivalence.

### 3.2. Performance Analysis

Since the \( \psi_{i,j} \)’s (and \( \phi_{i,j} \)’s) may be nonidentical, \( T \) does not necessarily follow a Chi-square distribution as those in [2] and [3]. Suppose that \( \psi_{i,j} \)’s have \( Q \) distinct values \( \{\nu_1, \cdots, \nu_Q\} \), where the multiplicity of \( \nu_n \) is \( q_n \), and \( \sum_{n=1}^{Q} q_n = N_t N_r \). With the PDF of the moment generation function (MGF), the distribution of \( T \) under \( \mathcal{H}_0 \) follows a Gamma mixture [7]
\[
f(t|\mathcal{H}_0) = \sum_{n=1}^{Q} \sum_{m=1}^{q_n} A_{m,n} f_G(t; m, 2\nu_n),
\]
where the \( A_{m,n} \)’s are constants satisfying \( \sum_{n=1}^{Q} \sum_{m=1}^{q_n} A_{m,n} = 1 \), and
\[
f_G(t; m, 2\nu_n) = \frac{t^{m-1} e^{-\nu_n t}}{(m-1)! (2\nu_n)^m}, \quad t > 0
\]
denotes the Gamma pdf. Define
\[
M_n(s) = \prod_{p=1}^{Q} \prod_{p 
eq n} \left( 1 - \frac{1}{(2\nu_p)^s} \right)^{q_p},
\]
and hence the \( A_{m,n} \)’s can be obtained via [7]
\[
A_{m,n} = \frac{1}{(q_n - m)! (2\nu_n)^{q_n - m}} M_n^{(q_n - m)} \left( \frac{1}{2\nu_n} \right),
\]
where \( M_n^{(k)}(s) = \frac{\partial^k M_n(s)}{\partial s^k} \). As a result, the probability of the false alarm rate is
\[
P_f(\eta) = 1 - \int_{0}^{\eta} f(t|\mathcal{H}_0) dt
= 1 - \sum_{n=1}^{Q} \sum_{m=1}^{q_n} A_{m,n} \int_{0}^{\eta} f_G(t; m, 2\nu_n) dt
= 1 - \sum_{n=1}^{Q} \sum_{m=1}^{q_n} A_{m,n} \gamma(m, \eta/(2\nu_n)) / (m-1)!,
\]
where \( \gamma(m, \theta) \Leftrightarrow \int_{0}^{\theta} t^{m-1} e^{-t} dt \) denotes the lower incomplete Gamma function.

Based on (10), \( \phi_{i,j} \)’s have \( Q \) distinct values \( \{\mu_1, \cdots, \mu_Q\} \) too. Let \( \nu_n = \mu_n \sigma_w^2 / (\sigma_p^2 + \mu_n \sigma_p^2) \), and then the multiplicity of \( \nu_n \) is \( q_n \). Similarly, the probability of detection is
\[
P_d(\eta) = 1 - \sum_{n=1}^{Q} \sum_{m=1}^{q_n} A_{m,n} \gamma(m, \eta/(2\mu_n)) / (m-1)!,
\]
where the \( A_{m,n} \)’s are functions of the \( \mu_n \)’s and can be obtained similarly as \( A_{m,n}^{(k)} \)’s. With \( P_f(\eta) \) and \( P_d(\eta) \), the receiver operation characteristic (ROC) is available.
3.3. Special Cases

Let all $\psi_{i,j}$’s have different values, we have $Q = N_t N_r$, and $q_n \equiv 1$ for all $n$. Therefore, (15) degenerates to [10, p.152]

$$
\bar{P_f}(\eta) = 1 - \sum_{n=1}^{Q} A_i^{0} \int_{0}^{2\tau/n} e^{-t} dt = \sum_{n=1}^{Q} A_i^{0} e^{-\frac{2\tau}{n} n},
$$

where $A_i^{0} = \prod_{p=1,p\neq n}^{Q} \frac{1}{1 - \psi_{i,p}/\nu_n}$ is explicit [10].

In addition, if all $\psi_{i,j}$’s share the same value $\nu$, we have $Q = 1$, and $q_0 = N_t N_r$. Based on (14), it is easy to see that $A_i^{0} = 1$ and $A_{m,0} = 0$ for $1 \leq m \leq N_t N_r - 1$. Thus $f(t|\mathcal{H}_0)$ is reduced as

$$
f(t|\mathcal{H}_0) = f_G(t; N_t N_r, 2\nu) = e^{2\nu N_t N_r - 1} e^{-\frac{2\nu}{N_t N_r - 1}} (2\nu)^{N_t N_r - 1}. \tag{18}
$$

Apparently, $T|\mathcal{H}_0 \sim \nu X^2_{2(N_t N_r)}$ [10], and this coincides with that in [2]. The analysis of probability of detection is similar.

4. SADDLEPOINT APPROXIMATION

PFE is a key ingredient of exact performance analysis. The calculation of the $A_i^{0}$’s is complex if the multiplicity is high. In addition, PFE is numerically sensitive [8]: an incorrect judgement on whether $\psi_{i,j} = \psi_{i,m}$ may result in considerable errors, especially when two coefficients are close. In the following, a SA [9] based performance analysis is suggested, and it is insensitive to numerical errors. The SA is a powerful tool to obtain the distribution of finite mixture of random variables, and it is very accurate in handling tail-probability.

The theory of SA is complex; however, the use of it is fairly straightforward. Since the MGF of the pdf of $z_{i,j}$ is $G_s(s) = \frac{1}{1 - 2s}$, where $s < \frac{1}{2}$ [10], that for the pdf of $(\psi_{i,j} z_{i,j})$ is $G_{\psi_{i,j}}(s) = G_s(\psi_{i,j} s) = \frac{1}{1 - 2\psi_{i,j} s}$, where $s < \frac{1}{2\psi_{i,j}}$ [10]. As a result, the MGF of $T$ under $\mathcal{H}_0$ is

$$
G_{T|\mathcal{H}_0}(s) = \prod_{j=1}^{N_t} \prod_{i=1}^{N_r} \frac{1}{1 - 2\psi_{i,j} s},
$$

where $s < \frac{1}{2\max_{i,j} \psi_{i,j}}$, and $\psi_{i,j} \triangleq \max_{i,j} \{\psi_{i,j}\}$. The cumulant generating function (CGF) of $T$ under $\mathcal{H}_0$ is defined as

$$
K_{T|\mathcal{H}_0}(s) = \log G_{T|\mathcal{H}_0}(s) = - \sum_{j=1}^{N_t} \sum_{i=1}^{N_r} \log(1 - 2\psi_{i,j} s). \tag{20}
$$

Suppose that $\hat{s}(t)$ is the solution of the saddlepoint equation

$$
K'_{T|\mathcal{H}_0}(s) \triangleq \frac{\partial K_{T|\mathcal{H}_0}(s)}{\partial s} = \sum_{j=1}^{N_t} \sum_{i=1}^{N_r} \frac{2\psi_{i,j}}{1 - 2\psi_{i,j} s} = t, \tag{21}
$$

where $t > 0$, and then the SA of $f(t|\mathcal{H}_0)$ is

$$
\hat{f}(t|\mathcal{H}_0) = \frac{1}{\sqrt{2\pi K''_{T|\mathcal{H}_0}(\hat{s}(t))}} \exp(K_{T|\mathcal{H}_0}(\hat{s}(t)) - t\hat{s}(t)). \tag{22}
$$

Integrating $\hat{f}(t|\mathcal{H}_0)$ from 0 to $t$, its cumulative distribution function (cdf) is written as [9, p.12]

$$
\hat{F}_T(t|\mathcal{H}_0) = \begin{cases} 
\Phi(r) + \varphi(r)\left(\frac{1}{r} - \frac{1}{\nu} \right), & t \neq \mathbb{E}(T|\mathcal{H}_0) \\
\frac{1}{2} + \frac{K''_{T|\mathcal{H}_0}(0)}{6\pi} s, & t = \mathbb{E}(T|\mathcal{H}_0),
\end{cases} \tag{23}
$$

where $K''_{T|\mathcal{H}_0}(s)$ denotes the third-order derivatives of $K_{T|\mathcal{H}_0}(s)$ with respect to $s$, $\Phi(t)$ and $\varphi(t)$ are respectively the cdf and pdf of the standard normal distribution,

$$
r = sgn(\hat{s}(t)) \sqrt{2t\hat{s}(t) - 2K_{T|\mathcal{H}_0}(\hat{s}(t))},
$$

and $sgn(.)$ represents the sign function. Finally, the approximate probability of false alarm rate is

$$
\hat{P_f}(\eta) = 1 - \hat{F}_T(\eta|\mathcal{H}_0). \tag{25}
$$

Similarly, the probability of detection with SA is

$$
\hat{P_d}(\eta) = 1 - \hat{F}_T(\eta|\mathcal{H}_1), \tag{26}
$$

where $\hat{F}_T(\eta|\mathcal{H}_1)$ is obtained similar to $\hat{F}_T(\eta|\mathcal{H}_0)$.

The SA method provides an accurately pointwise rather than a roughly asymptotic approximation. This part answers two questions related to (21): whether the saddlepoint solution exists? and whether it is unique? Since $0 < K''_{T|\mathcal{H}_0}(s) < +\infty$ for $s \in \mathbb{V} \triangleq (-\infty, \frac{1}{2\max_{i,j} \psi_{i,j}})$, $K''_{T|\mathcal{H}_0}(s)$ is a continuous and monotonically increasing function in $\mathbb{V}$. Since

$$
\lim_{s \to -\infty} K''_{T|\mathcal{H}_0}(s) = 0 \quad \text{and} \quad \lim_{s \to \frac{1}{2\max_{i,j} \psi_{i,j}}} K''_{T|\mathcal{H}_0}(s) = +\infty, \tag{27}
$$

we obtain $0 < K''_{T|\mathcal{H}_0}(s) < +\infty$. Thus, $K''_{T|\mathcal{H}_0}(s)$ and $t$ share the same range, and the solution of (21) exists. Furthermore, due to monotonicity, the solution is unique.

![Fig. 1. The ROCs for MIMO radar systems with different system parameters. The simulated, exact, and approximate curves are overlapping for the parameter set A, while the ‘exact formula’ suffers from significant numerical errors for the second set. Each simulated curve is obtained with $1 \times 10^6$ runs.](image-url)
5. POWER ALLOCATION

The optimal power allocation strategy will maximize the probability of detection for a given false alarm rate $c_1$

$$\max_{\mathbf{E}} P_d(\eta), \text{ s.t. } P_f(\eta) = c_1 \text{ and } \mathbf{E}^T \mathbf{1} \leq \bar{E},$$  \hspace{1cm} (28)

where $\mathbf{E} \triangleq [E_1, \ldots, E_N]^T$, and $\mathbf{1}$ is an all-one vector with proper size. Since $P_d(\eta)$ and $P_f(\eta)$ are complicated functions of $\mathbf{E}$, the optimization of (28) is difficult. Here, a suboptimal strategy is obtained by maximizing the Kullback-Leibler divergence

$$\max_{\mathbf{E}} \mathcal{D}(f(\mathbf{x}|\mathbf{H}_0)||f(\mathbf{x}|\mathbf{H}_1)), \text{ s.t. } \mathbf{E}^T \mathbf{1} \leq \bar{E},$$  \hspace{1cm} (29)

where $\mathbf{x}$ collects all $x_{i,j}$’s. Since $x_{i,j}$’s are independent under both hypotheses, $\mathcal{D} \triangleq \mathcal{D}(f(\mathbf{x}|\mathbf{H}_0)||f(\mathbf{x}|\mathbf{H}_1))$ is specified as

$$\mathcal{D} = \int f(\mathbf{x}|\mathbf{H}_0) \log \left( \frac{f(\mathbf{x}|\mathbf{H}_0)}{f(\mathbf{x}|\mathbf{H}_1)} \right) d\mathbf{x} $$

$$= \sum_{i=1}^{N_1} \sum_{j=1}^{N_2} \left[ \log(1 + E_i \sigma_w^2 \sigma_g^2 p_{i,j}^2) + \frac{1}{1 + E_j \sigma_w^2 \sigma_g^2 p_{i,j}^2} - 1 \right].$$

Even though (30) is neither convex nor concave, the complexity of (29) is much lower than (28). One can use brute-force search to obtain the optimal solution of (30).

6. NUMERICAL RESULTS

This part gives two examples to exhibit the accuracy of the exact and approximated results with the help of ROCs. For simplicity, we set $\sigma_w^2 = \sigma_g^2 = 1$ and $E_i = 3$ for all $i$. The propagation losses are obtained via $p_{i,j} = [P]_{i,j}$, where $\mathbf{P} = \mathbf{p}_t \times \mathbf{p}_r^T$, while $\mathbf{p}_t$ and $\mathbf{p}_r$ correspond to the transmission and receiving units, respectively, as shown in (1). Two parameter sets, say $A$ and $B$, are that

- $N_1 = 2, N_2 = 3, \mathbf{p}_t^A = [1, 1]^T$, and $\mathbf{p}_r^A = [0.6, 0.8, 0.9]^T$;
- $N_1 = 2, N_2 = 3, \mathbf{p}_t^B = [1, 1.000001]^T$, and $\mathbf{p}_r^B = \mathbf{p}_r^A$.

The obtained ROCs are collected in Fig.1, where the ‘suboptimal curve’ indicates the detector ignoring the propagation loss diversity [2] [3]. Clearly, integrating propagation losses into the MIMO radar will significantly improve system performance. From Fig.1 (a), we see that the simulated, exact, and approximate ROCs are almost overlapping as the distinction of weighting coefficients are clear. However, if they are very close, the numerical errors will significantly degrade its accuracy of the ‘exact formula’, while the approximate one is relatively unaffected.

Secondly, the probability of detection as a function of SNR will be analyzed for a given false alarm rate $10^{-3}$. The results for optimal and uniform power allocation strategy are shown in Fig.2, where (a) utilizes the parameter set A, while (b) utilizes the parameter set C:

- $N_1 = 3, N_2 = 3, \mathbf{p}_t^B = [0.1, 0.8, 1]^T$, and $\mathbf{p}_r^B = [0.2, 0.7, 1]^T$.

Even though the transmission gains of set A are the same, the system will (optimally) allocate all its power to a single transmitter for set A when the SNR is low. This coincides with the result that a statistical MIMO radar is not as good as a multistatic radar—a system with one transmitter and multiple distributed receivers—at low SNR without considering propagation losses [2]. For set C, all propagation losses are distinct. Optimally allocating the transmission power according to (29) can significantly improve the system performance within a wide range of SNR value. In addition, if the SNR is very large, the probability of detection will go to one for both strategies.

7. CONCLUSIONS

This paper integrated the propagation losses into the MIMO radar signal model. Since the propagation losses are functions of geometry and system parameters, they may not share the same value for different paths. As a result, the path gains are not identically distributed any more. In this paper, we derived the test statistics for the binary hypothesis test, and analyzed the detector performance. The exact performance formulas require less computation than the SA, as the latter involves two optimizations for every sample of a ROC curve. For a special case that weighting coefficients are very close, the former may be numerically sensitive, while the latter is robust.

8. REFERENCES


